Using Neural Networks to Improve the Performance of Radiative Transfer Modeling Used for Geometry Dependent Surface Lambertian-equivalent Reflectivity Calculations

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Introduction

- Surface Lambertian-equivalent reflectivity (LER) is important for trace gas retrievals in the direct calculation of cloud fractions and indirect calculation of the air mass factor
- Current trace gas retrievals use climatological surface LER's
- Surface properties that impact the bidirectional reflectance distribution function (BRDF) as well as varying satellite viewing geometry can be important for retrieval of trace gases
  - Geometry Dependent LER (GLER) captures these effects with its calculation of sun normalized radiances (I/F) and can be used in current LER algorithms (Vasilkov et al. 2016)
- Pixel by pixel radiative transfer calculations are computationally expensive for large datasets
- Modern satellite missions such as the Tropospheric Monitoring Instrument (TROPOMI) produce very large datasets as they take measurements at much higher spatial and spectral resolutions
- Look up table (LUT) interpolation improves the speed of radiative transfer calculations but complexity increases for non-linear functions
- Neural networks perform fast calculations and can accurately predict both non-linear and linear functions with little effort

Methods

- I/F was calculated using the vector linearized discrete ordinate radiative transfer model (VLIDORT) for Ozone Mapping Instrument (OMI) viewing geometry
- LUT interpolation was performed using linear interpolation across several dimensions
- Neural networks were trained on the same dimensions as LUT Interpolation

Land LUT Nodes (Schaaf et al. 2002)	Node Range	Approximate Spacing
Geometric Coefficient*	0.0-0.1	Every 0.01
Volumetric Coefficient*	0.0-0.5	Every 0.05
Isotropic Coefficient*	0.0-1.0	Every 0.05
Solar Zenith Angle	0-86 Degrees	Every 3 Degrees
Relative Azimuth Angle	0-180 Degrees	Every 5 Degrees
Viewing Zenith Angle	0-80 Degrees	Every 3 Degrees
Surface Pressure	411-1100 mb	Every 75 mb

* MODIS BRDF Coefficient

Ocean LUT Nodes (Mishchenko et al. 1997)	Node Range	Approximate Spacing
Wind Speed	0.0-24.0 m/s	Every 2 m/s
Chlorophyll Concentration	0.0-10.0 mg/m^3	Every 0.5 mg/m^3 (log(CHL))
Solar Zenith Angle	0-86 Degrees	Every 2 Degrees
Relative Azimuth Angle	0-180 Degrees	Every 5 Degrees
Viewing Zenith Angle	0-80 Degrees	Every 3 Degrees
Surface Pressure	411-1100 mb	Every 75 mb

Results

Ocean I/F with OMI Viewing Geometry 2006m0715 Orbit 10640

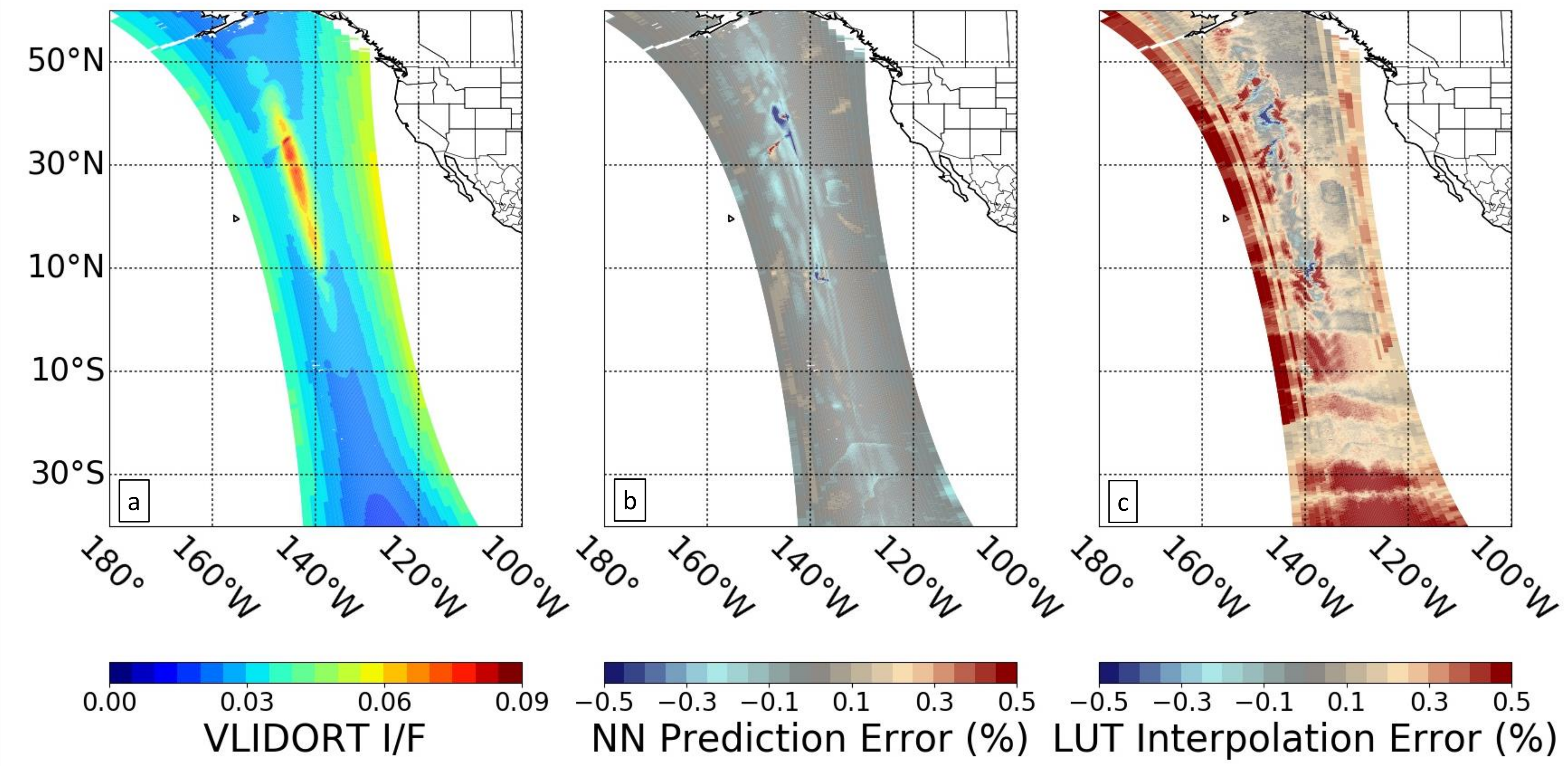

Figure 1: Maps showing sun normalized radiance (I/F) calculated for OMI viewing geometry by VLIDORT along with error from neural network & LUT interpolation when compared with VLIDORT as reference for orbit 10640 on July 15, 2006. a) Percent error of neural network; b) VLIDORT TOA Rad; c) Percent error of LUT interpolation

Ocean and Land I/F with OMI Viewing Geometry 2006m0715 All Orbits

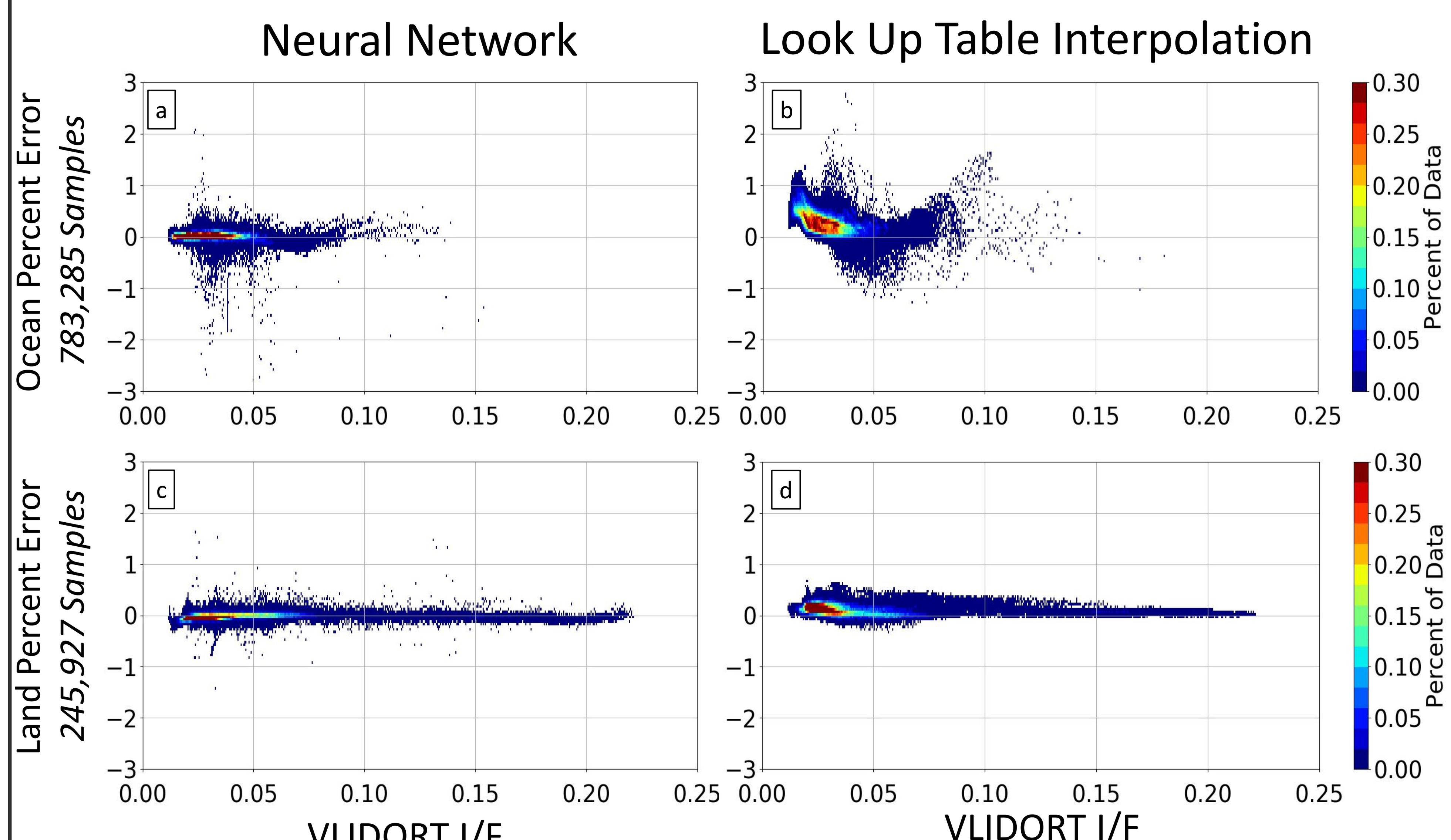

Figure 2: Plots showing the error of neural network and LUT calculations when compared to VLIDORT as reference on July 15, 2006. a) Percent error of neural network calculations over oceans; b) Percent error of LUT interpolation over oceans; c) Percent error of neural network calculations over land; d) Percent error of LUT interpolation over land

Analysis & Conclusion

Ocean I/F

	Neural Network	LUT Interpolation
Mean Absolute Error	1.30 * 10^{-5}	7.36 * 10^{-5}
Root Mean Squared Error	2.72 * 10^{-5}	4.29 * 10^{-5}
Daily Processing Time	10.4 seconds	79.0 seconds

Land I/F

	Neural Network	LUT Interpolation
Mean Absolute Error	1.79 * 10^{-5}	4.43 * 10^{-5}
Root Mean Squared Error	3.76 * 10^{-5}	6.10 * 10^{-5}
Daily Processing Time	11.2 seconds	61.7 seconds

Table 1: Statistical error calculating sun normalized radiances (I/F) for neural network & LUT interpolation with VLIDORT I/F as a reference and approximate computational time to calculate a full day of orbits

- The neural network showed a mean absolute error and root mean squared error smaller than LUT interpolation over the oceans and land (Table 1)
- Computational time was significantly improved using a neural network instead of LUT interpolation (Table 1)
- Over oceans and land the LUT interpolation showed a systematic high bias at low TOA Rad while the neural network shows no systematic biases (Figure 2)
- The neural network produced more noise at extreme node values, especially over land (Figure 2)

Future Work

- Improve accuracy at extreme input node values by incorporating smart sampling, which determines most ideal training data based on histograms of real data (Loyola et al. 2016)
- Exercise the current neural network method with computationally intensive datasets such as TROPOMI

References

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